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A Novel Approach to Calibrating Wavemakers and Generating Wavemaker Transfer Functions

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NOMENCLATURE

AAM…………Average Angle Measure
FFNN………..Feed Forward Neural Network
ICE……………Intelligent Calculation of Equations
MASK……….Maneuvering and Seakeeping Basin
ONR…………Office of Naval Research
RNN…………Recursive Neural Network
SNOW……….Simulation of Non-Linear Ocean Wave-Field

ABSTRACT

Limitations in our current knowledge of a ship in extreme wave conditions have been illuminated by the work being done by the US Navy on advanced hull-forms. Stochastic approaches to these phenomena are insufficient, and deterministic testing of these events must be performed if the physics is to be understood. Although modern computer controlled wavemakers provide the ability to generate regular sine waves, long crested multi-spectral waves, mixed seas of almost any sea spectra, and even "freak" waves, all of these systems require the wavemakers be tuned to the specific facility and that transfer functions between wavemaker settings and the generated wave be calculated. This tuning is performed to compensate for the facility's geometry, wave absorbers (beaches), etc, as well as to aid the researcher in using the wavemaker system.

The Maneuvering and Seakeeping (MASK) basin at the Naval Surface Warfare Center, Carderock Division (NSWCCD) is a large rectangular basin, measuring 240 feet (73.2 m.) by 360 feet (109.7 m.). Two adjacent walls of the MASK are equipped with pneumatic wavemakers, while the other two banks are equipped with wave absorbing beaches. This report describes the development of a feed-forward neural network model of the MASK wavemakers and demonstrates the utility of this approach in calibrating wavemakers and generating wavemaker transfer functions.

ADMINISTRATIVE INFORMATION

The work described in this report was performed by the Maneuvering and Control (Code 5600) Division of the Hydromechanics Department at the Naval Surface Warfare Center, Carderock Division (NSWCCD). The work was sponsored by the Office of Naval Research under the direction of ONR Program Manager Dr. L. Patrick Purtell (Code 33).

INTRODUCTION

The Naval Surface Warfare Center Carderock Division (NSWCCD) is a government owned facility that conducts tests on large-scale naval models. Three of its test basins, the Maneuvering and Seakeeping Basin (MASK), the Deep Water Basin, and the High Speed Basin, are equipped with pneumatic wavemakers. Recent work on advanced hull-form concepts, as well as a wave slam incident of the SeaFighter, FSF-1, illustrates the need for increased study of ships in extreme wave conditions. Stochastic analysis approaches to these phenomena are insufficient, and deterministic testing of these events must be performed if the physics is to be understood. Although modern wavemakers provide the ability to generate most, if not all, types of waves, all of these wave generation systems require tuning to the specific facility and the calculation of transfer functions between wavemaker settings and the generated wave. This tuning is performed to compensate for the facility's geometry, wave absorbers (beaches), etc., as well as to aid the researcher in using the wavemaker system. Because the ship motion

and capsize problem is fully coupled and nonlinear, it is essential that the waves be accurately created, and in a repeatable fashion.

For model testing, the desire would be to accurately recreate a measured sea state. This capability would allow the model basin to better correlate full-scale field measurements to model scale measurements and to create more realistic sea states. Figure 1 shows the SeaFighter, FSF-1, high-speed catamaran. Figure 2 shows the wave spectrum measured during one period of field test of the SeaFighter and Figure 3 is an image of the model of the vessel as it was tested in the MASK. It would obviously be desirable to recreate the full scale spectrum while model testing in the MASK (Figure 2).

Figure 1: SeaFighter, FSF-1, High-Speed Catamaran.

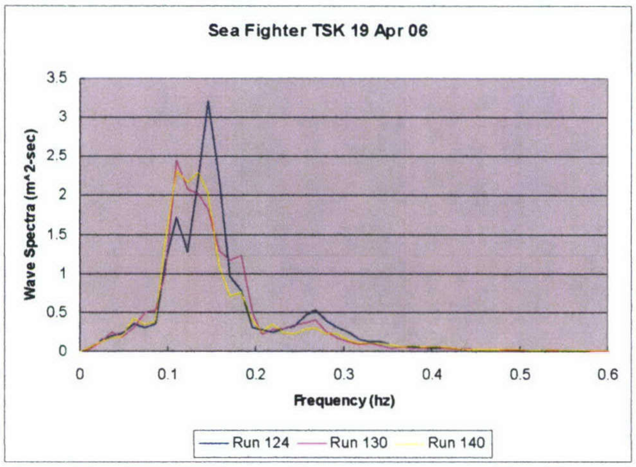

Figure 2: Wave Spectra for 19 April 2006, when the SeaFighter was undergoing rough water trials.

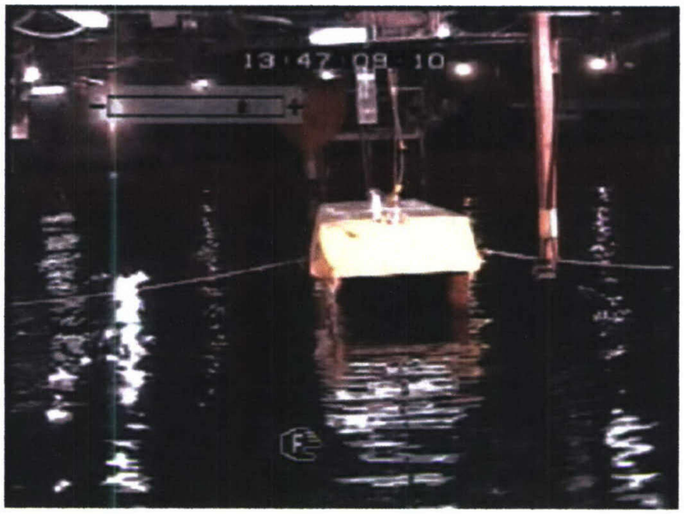

Figure 3: An image of the NSWC model of the SeaFighter being tested in the MASK.

The standard calibration procedures used for tuning a wave generation system are based upon empirically determining the wavemaker response function, specifically the characteristic of the generated waves as a function of input frequency, amplitude, and phase angle. This work is typically done by measuring the generated wave over the range of wavemaker inputs and generating empirical curve fit transfer functions. Naito (1) presents a summary of the theory of wave generation in wave basins, and Longo, et. al. (2) describes the Iowa Institute of Hydraulics Research's wavemaker and the calibration procedures they utilized.

Currently in the MASK, wave characteristics are determined by examining a table of previous wavemaker settings and corresponding wave heights compiled by Stahl (3). Wavemaker settings are determined from these tables/plots and are then verified by actual measurement of the generated wave field. This process is not only awkward, but in some cases requires multiple iterations before the desired waves/sea states are formed. By employing a feed-forward neural network to model the wave generation, a more accurate set of "transfer functions" can be generated.

Though the application of a feed-forward neural network is a new approach to modeling wave generation, the modeling of waves by neural networks is not. Wu (4) proposed the implementation of a strictly deterministic solution to model the evolution of a large-scale nonlinear ocean wave-field. The proposed model would be physics based and use phase-resolved simulations to model wave interactions. Wu (4) introduced the computational modeling method known as the Simulation of Non-Linear Ocean Wave-field (SNOW). This deterministic model accurately predicted wave-field statistics for evolving ocean waves as well as essential characteristics of ocean waves during wave evolution. Building upon the initial successes of the method proposed in Wu (4), Yue (5) proposed a comprehensive real-time prediction method to accurately forecast the local wave-field around the hull of a ship. The ultimate goal of this real-time predictor was implementation in an automated or assisted steering system for ships. In the proposed solution, local wave heights, for an area approximately 1 km^2 could be obtained using

technology such as radar or LiDAR. This information would then be used to project the evolution of the wave-field approximately 20 seconds in advance.

Both simulations presented by Wu (4) and Yue (5) produced successful solutions for accurately predicting wave field information based upon initial data. However, despite the success in the accuracy of the models, they are both computationally intensive. The deterministic model of the evolution of a wave-field surrounding a surface ship runs on the order of 10^2 to 10^4 times slower than real-time (5). This long processing time makes deterministic models inefficient as well as ineffective methods for wave height prediction on the order of 10^2 times faster than real-time. Additionally, in order to be implemented in a real-time decision making system, algorithms to predict the response of the vessel in the predicted wave field and to actually control the motion of that vessel in a reasonable time would have to be produced. Despite the fact that a fully deterministic model of the waves generated in the MASK could be developed following the method outlined by Yue, this method is impractical for use in generating wave maker operational guidance and transfer functions.

FACILITIES

Figures 4 and 5 show the Maneuvering and Seakeeping Basin (MASK), which measures 240 feet (73.2 m.) by 360 feet (109.7 m.) at the Naval Surface Warfare Center, Carderock Division. The MASK is a large rectangular test basin, equipped with wavemakers along the north and west walls and is used to conduct experiments on both remote controlled models (RCMs) and captive models. The north side, or Long Bank, has thirteen wavemaker units, and the west side, or Short Bank, has eight wavemaker units. Each of the wavemaker units can be operated individually though they also are normally operated in unison. The other two banks of the MASK are equipped with wave absorbing beaches to minimize the effects of reflections off the basin walls.

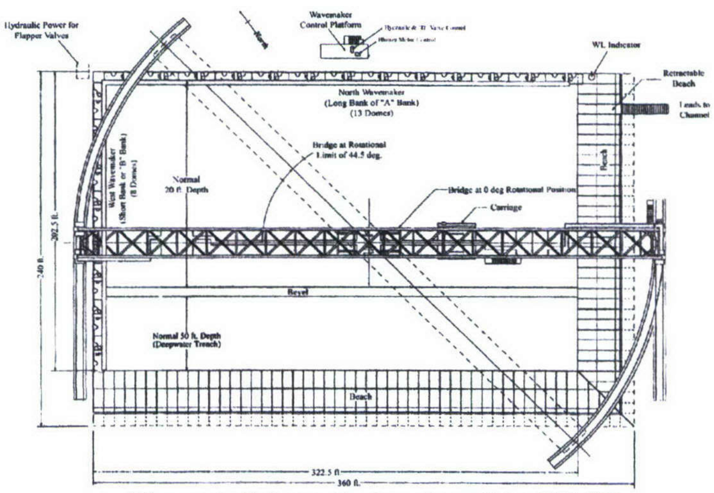

Figure 4: Schematic drawing of the MASK.

Figure 5: The MASK at the Naval Surface Warfare Center, Carderock Division.

WAVEMAKERS

Waves in the MASK are generated by pneumatic wavemakers, which use air pressure to drive a column of air perpendicular to the free surface in a periodic motion. It is the movement of this air column that transfers energy from the wavemaker to the water, creating waves. The downward movement of this air column causes the water level in the basin immediately outside the dome of the wavemaker to rise, creating a wave crest (Figure 6). Alternatively, an upward movement of the air column causes the water level in the basin immediately outside the dome of the wavemaker to fall, creating a wave trough (Figure 7). The motion of the air column is controlled by a pair of flappers, which serve to either increase or decrease the air pressure inside the dome, depending on their orientation. The flappers are located between an electric blower and the dome of the wavemaker (Figure 8). As the flappers oscillate, the airflow is either directed from the outside into the dome (Figure 9), thus increasing the pressure and causing a downward movement of the air column, or airflow is directed out of the dome, thereby causing a decrease in air pressure, and a corresponding upward movement of the air column (Figure 10). The period of oscillation of the flappers determines the period of the resulting wave.

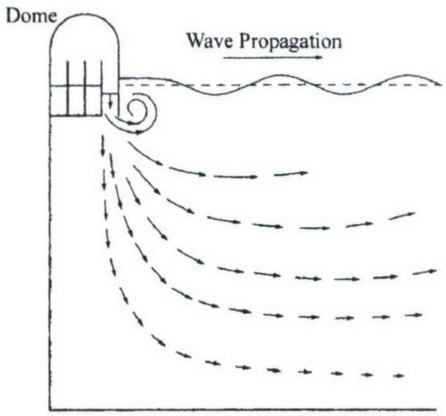

Figure 6: The dominant oscillatory component of a wavemaker downstroke (3).

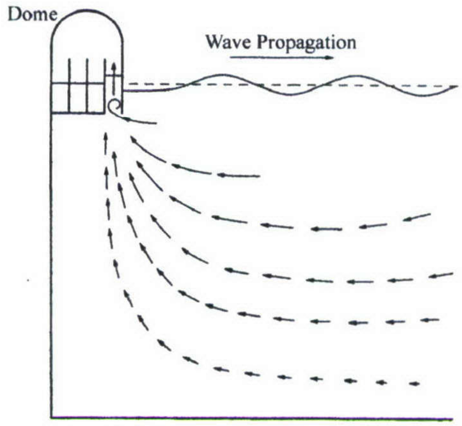

Figure 7: The dominant oscillatory component of a wavemaker upstroke (3).

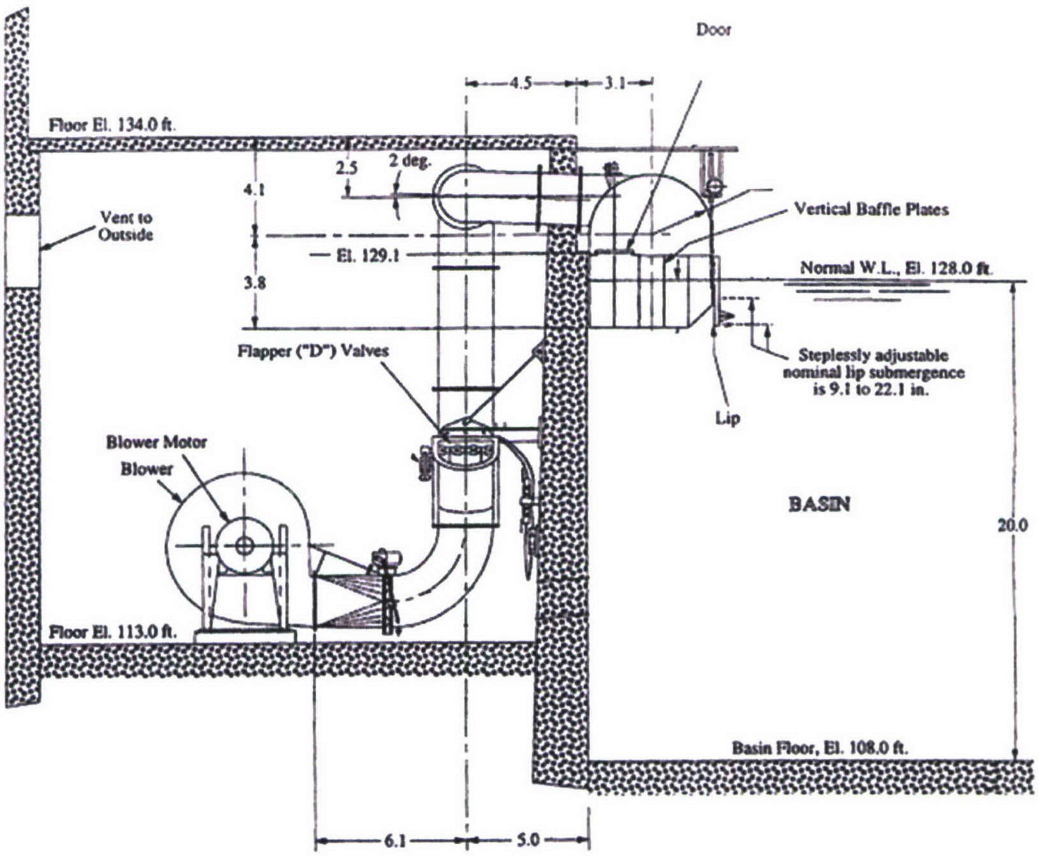

Figure 8: A schematic diagram of a MASK Short Bank wavemaker (3).

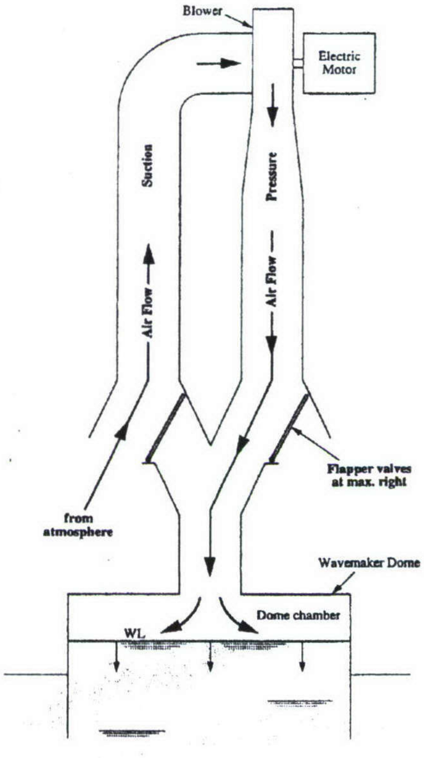

Figure 9: Airflow downstroke diagram (3).

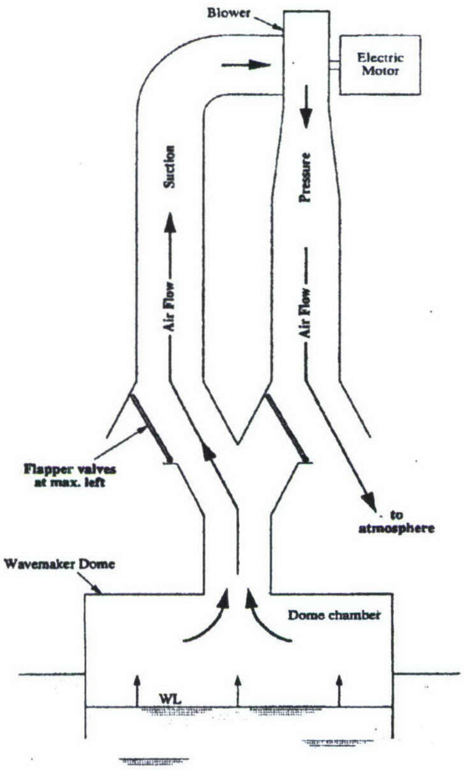

Figure 10: Airflow upstroke diagram (3).

The amplitude of the resulting wave is determined by several factors. These factors include the speed of the blower feeding the wavemaker, the period of the wave, the lip depth, and the door settings. However, as noted by Stahl (3), the effect of the door settings was found to be minimal and the doors were removed from the Long Bank wavemakers. The dominant factor in determining wave height is the speed of the electric blower. The depth below the water's surface of the wavemaker's lip can be adjusted and acts as a filter, but this is not thought to significantly affect wave height.

Currently, wave heights are predicted by examining a table of previous wavemaker settings and corresponding wave heights, compiled in Stahl (3). By plotting these points in graphical form, certain trends can be discerned, allowing for reasonable predictions of wave heights to be made. However, the data provides only maximum wave height for given wavemaker settings. This method allows for reasonable predictions of regular waves to be made but only provides rough guidance for generating irregular waves. Wavemaker settings for irregular waves are determined from these tables/plots and are then verified by actual measurement of the generated wave field. This process is not only awkward, but in some cases requires multiple iterations before the desired waves are formed.

NEURAL NETWORKS

The Neural Network Development Laboratory was established at NSWCCD in 1994 with the directive to apply neural network technology as a predictive tool to problems of interest to the Navy. Since 2000, NSWCCD has continued these efforts within the Maneuvering & Control Division in cooperation with Applied Simulation Technologies.

A neural network is a computational method for producing a nonlinear model of a given data set that relates input variables to output variables. In a feedforward neural network (FFNN) information travels from input nodes through internal groupings of nodes (hidden layers) to the output nodes. This type of model works well for data sets where the outputs are determined solely by the inputs and previous conditions have little effect on the current state. A FFNN is distinguished from a recursive neural network (RNN) by the fact that the latter employs feedback; namely, the information stream issuing from the outputs is redirected to form additional inputs to the network. The additional complexity of an RNN is required for the solution of difficult time-dependent problems such as the simulation of the motion of a maneuvering submarine (6) or surface ship (7). The neural network program used for this work was "Intelligent Calculation of Equations" (ICE), developed by William Faller of Applied Simulation Technologies (8).

Data are fed into the neural network through the input nodes, undergoes processing in the hidden (internal) layers of the network, and finally leaves the network through the output nodes (Figure 11). The processing that occurs in the hidden layers of the network refers to the system of gains and transfer functions, which take place inside the network. Every connection between each node of one layer to each node of the next

has an associated weight. As information travels along these connections it is multiplied by the associated gains before it is presented to the next layer of nodes. Each of the receiving nodes combines the weighted information by using a nonlinear activation (transfer) function, typically some variation on hyperbolic tangent. This transfer function returns a value between zero and one, which is then sent on to the next layer of weights and nodes. During the training process, the outputs of the neural network are compared to the target output vector and the error between the predicted and actual outputs is calculated. The weights are then adjusted accordingly in an effort to minimize the error between the predicted vector and the target output vector. This process is repeated iteratively in order to minimize error for all input and target output vectors in the data set. When the solution with the minimum error is found, the training is complete and the weights are saved. The algorithm used to train the neural network is known as backpropagation and uses the method of gradient descent. While the backpropagation algorithm can be very time consuming, the prediction time for the neural network is very short, typically measured in milliseconds (10).

NSWCCD has previously implemented neural networks to solve other complex naval problems, developing new techniques in the process. The technique of using neural networks as virtual sensors was introduced in Hess et al (10). This technique presents a method for the interpolation of data points when complete data sets are not readily available. According to Hess, by training on available data, introduced as input vectors, a neural network should be able to provide accurate estimates for the segments of the desired data set for which real data were unattainable. After the data set is reconstructed, the new "complete" data set can be fed into the neural network as input vectors, producing a final neural network prediction method for the full range of the desired data set. This implementation of neural networks is extremely useful in applications where the instrumentation is known to be inconsistent in providing readings.

Faller et al. (6) introduced a recursive neural network that predicted submarine maneuvers based on initial conditions and the control signal as well as the previous output vector. This allowed the neural network to learn of any delayed effects from the previous conditions, which are common when dealing with motion in water, and to make implicit calculations from the previous output vector. In the method proposed in Hess, six "basic values" (three values for position and three values for angle) from the ten previous input vectors, as well as the previous output vector, were fed back into the neural network as part of the current input vector. Based on the results in Hess, this amount of historical information was enough to make "good" (Average Angle Measurement value of 0.7-0.9) predictions of submarine motion. Increasing the amount of historical data provided to the neural network in the input vector should increase the accuracy of predictions, but does so at the cost of computation time.

The primary method for assessing the accuracy of the predictions of a neural network during training is the Average Angle Measure (AAM) (Appendix). This technique was developed by the Maneuvering Certification Action Team at NSWCCD to quickly determine how closely the neural network predicted values match the measured values for a time series (11). If the predicted value matches the measured value, the line

extending from the origin to the plotted point will have a slope of one. If the prediction does not exactly match the measured value, the point will fall on either side of the 45-degree line, and the line between the origin and the plotted point will have a slope either greater than or less than one. This angle provides a qualitative measure of the degree of error of the prediction. Therefore to determine the error of the entire prediction set, all of these angles should be averaged together. However, if the measured value is very small (<<1), even if the predicted value is very close to the measured value, a large angle may still be created. Likewise, if the measured value is very large (>>1) and the predicted value is far from the measured value, a small angle may be created. Therefore, the procedure for determining AAM weights each angle by the distance of the point from the origin (12).

The FFNNs used in this effort are fully connected with two hidden layers and use 0 to 1 binary sigmoid activation functions. Each FFNN has a single output to maximize prediction quality; therefore, problems with more than one dependent variable use multiple networks. The available experimental or numerical data was partitioned into two sets: training data (~80%) used to train the network and adjust the weights via backpropagation, and validation data (~20%) used along with the training data to test the performance of the trained network. Prediction quality is judged by two error measures: the average angle measure (AAM) described in (12; 9), and a correlation coefficient. For both measures, a numerical value of one indicates perfect agreement between measured data and predictions, whereas a value of zero denotes no agreement.

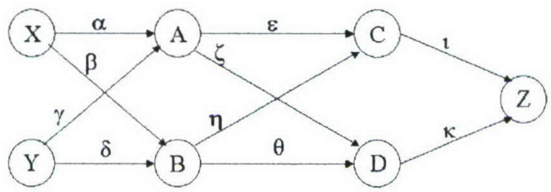

Figure 11: A diagram of a simple neural network with two input nodes, two hidden layers of two nodes, and one output node. The Greek letters represent the corresponding weights for each connection in the network.

RESULTS

The neural network implemented for this project was trained to predict the amplitude of regular waves created in the MASK and the wave energy within specific wave period bins for irregular waves.

In the case of regular waves, the inputs for the neural network are frequency and blower rpm and the output is wave height. The neural network was initially trained using historical data from waves produced by wavemakers on both the Short Bank and Long Bank in order to make a comprehensive prediction model for waves generated in the

MASK. The final neural network model was trained on data from just the Short Bank, which was obtained specifically for this purpose, providing a more accurate model of the waves being currently produced. The training and prediction sets were chosen so that each would contain the full range of blower speeds and frequencies.

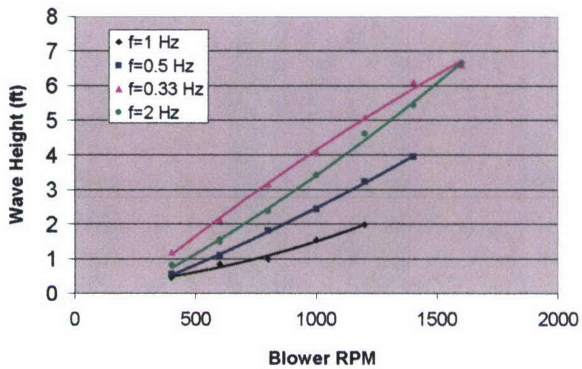

Figure 12: Blower RPM vs. Wave Height at each frequency for regular waves.

Figure 12 shows the measured wave height for the range of blower settings (frequencies and rpm) tested, where it is clear that the relationship between blower rpm, frequency and wave height is not linear. Figure 13 shows a comparison between the neural network predicted and the measured values of wave height. The AAM for this model was 0.92, and the R^2 value was 0.96, indicating the accuracy of the neural network model.

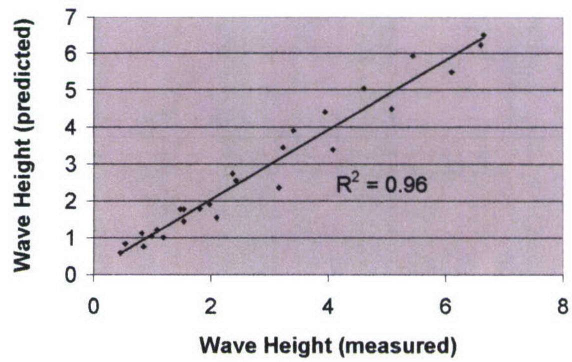

Figure 13: Wave height predictions from the FFNN for training and validation values for regular waves (AAM=0.92).

Since filtered white noise is used as the frequency input to the wavemakers when generating random or irregular waves the wave amplitudes in 6 period bins were summed for the filtered white noise and the wave height readings. The period bins were: 0-0.5s, 0.5-1s, 1-1.5s, 1.5-2s, 2-2.5s, and 2.5s and greater. The inputs to the feed forward neural network were blower speed (RPM), lip setting (up or down, input as 1 or 2), and the summed amplitudes from the filtered white noise bins 0-0.5s, 0.5-1s, 1-1.5s, 1.5-2s and 2 to 2.5s (2.5s+ was omitted because it was very close to zero for most cases). Figure 14 shows a typical set of summed filtered white noise values, specifically for blower speed = 800 rpm with the wavemaker lips up. The neural net model's output values were wave heights in the following period bins, 0.5-1s, 1-1.5s, 1.5-2s, 2 to 2.5s, 2.5s+ (0-0.5s was omitted because it was very close to zero for most cases). Figure 15 shows the results for

the summed wave height amplitudes over all period bins for all the irregular wave conditions tested, comparing the predicted to measured values. The AAM of this set of predictions was 0.84 (Figure 16). Blower speed varied from 800 to 1600 rpm and the wavemaker lips were run in both up and down positions (Figure 17). Several independent trials of several minutes each were run for each set of conditions.

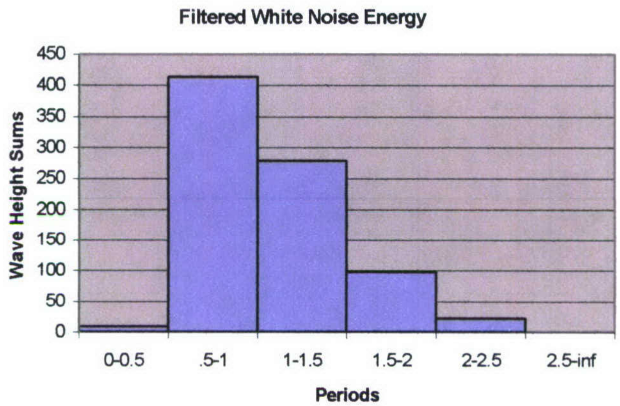

Figure 14: Filtered white noise amplitudes.

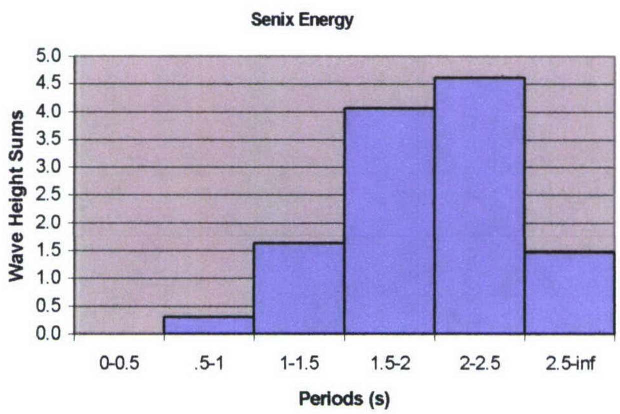

Figure 16: Measured wave height amplitudes.

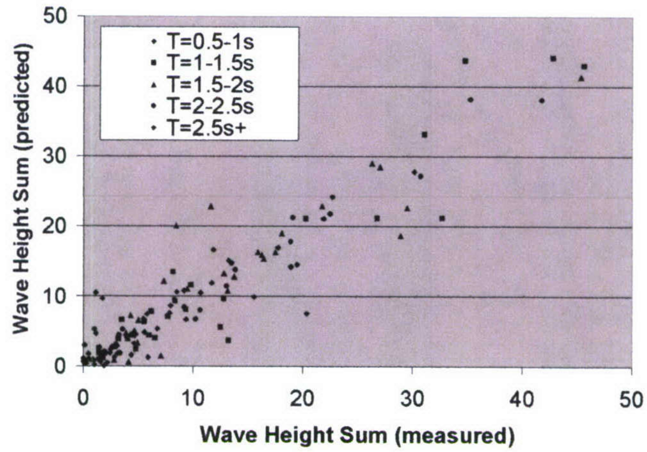

Figure 16: Wave height predictions from FFNN for training and validation values for irregular waves (AAM=0.84).

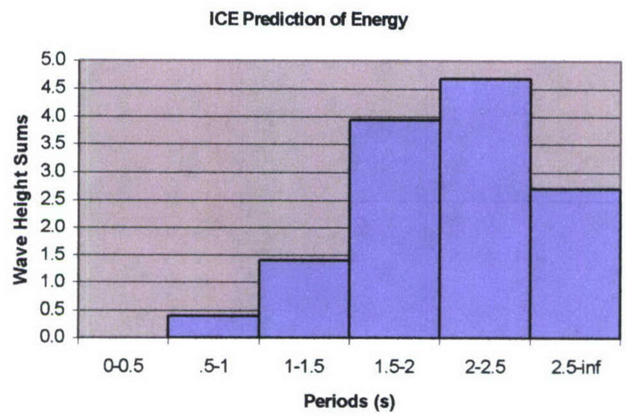

Figure 17: Predicted wave height amplitudes where the blower speed = 800 RPM and the wavemaker lips were up.

CONCLUSION

Overall, the use of feed forward neural networks to predict wave heights as a function of wavemaker inputs, i.e. to tune and generate nonlinear transfer functions for the wavemakers was very successful for both regular and irregular waves, with AAM values of 0.92 and 0.84 respectively. This capability decreases the time spent calibrating and verifying the wave field in the MASK before a given experiment. The ideal application of the neural network in this case would be as a method for a program in which the user would simply supply the desired wave height/sea state and the program would return the wavemaker inputs to obtain the targeted wave conditions. The program would call this neural network to predict wave height based on wavemaker settings and then use back propagation to find the optimum settings.

The ability to accurately predict wave heights also suggests the future application of a neural network model as a monitoring device for the wave generation system. By reading the wavemaker settings directly from the computer controlling the wavemaker, a neural network could be used in real time to make predictions of the wave heights for the generated waves. These predictions could then be compared to the resulting wave heights to determine if there was a significant discrepancy between the two values. If a large error between the two values did occur, the neural network could alert the user to the possibility of a problem in the wave making process.

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APPENDIX

The Average Angle Measure was developed by the Maneuvering Certification Action Team at NSWCCD in 1993-1994 (see July and August 1994 reports). This metric was created in order to quantify (with a single number) the accuracy of a predicted time series when compared with the actual measured time series. The measure had to satisfy certain criteria; it had to be symmetric, linear, bounded, have low sensitivity to noise and agree qualitatively with a visual comparison of the data.

$$
\begin{aligned}
AAM_j &= 1 - \frac{4}{\pi}\left[\frac{\sum_{n=1}^{N} D_j(n)\,|\,\alpha_j(n)\,|}{\sum_{n=1}^{N} D_j(n)}\right], \\
\alpha_j(n) &= \cos^{-1}\left[\frac{|\,m_j(n) + p_j(n)\,|}{\sqrt{2}\,D_j(n)}\right], \qquad \text{(A1)} \\
D_j(n) &= \sqrt{m_j^2(n) + p_j^2(n)}\ ,
\end{aligned}
$$

The definition is given in Eq. A1 for the j^{th} output variable computed over a set of N points and is described as follows. Given a predicted value, p, and an experimentally measured value, s, one can plot a point in p-s space as shown in Figure 18.

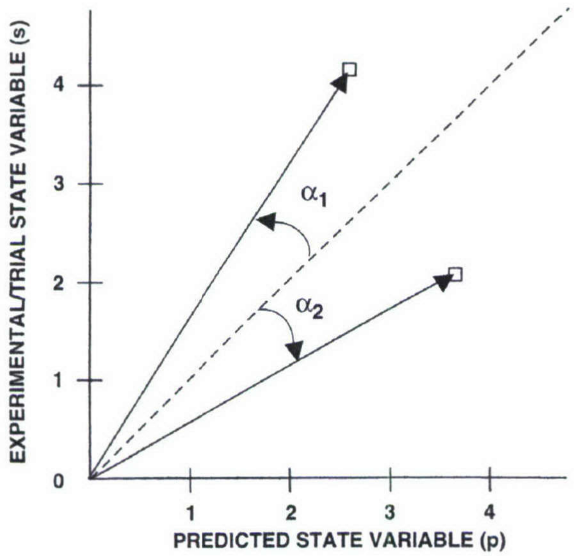

Figure 18: Definition of the Average Angle Measure

If the prediction is perfect, then the point will fall on a 45° line extended from the origin; the distance from the origin will depend upon the magnitude of s. If $p \neq s$, the point will fall on one side or the other of the 45° line. If one extends a line from the origin such that it passes through this point, one can consider the angle between this new line and the 45° line, measured from the 45° line. This angle is a measure of the error of

the prediction. To extend this error metric to a set of N points, one computes the average angle of the set. A problem arises, however. When s is small and p is relatively close to s, one may still obtain a comparatively large angle. On the other hand, when s is large and p is relatively far from s, one may obtain a relatively small angle. To correct this, the averaging process is weighted by the distance of each point from the origin. The statistic is then normalized to give a value between –1 and 1. A value of 1 corresponds to perfect magnitude and phase correlation, -1 implies perfect magnitude correlation but 180° out of phase and zero indicates no magnitude or phase correlation. This metric is not perfect; it gives a questionable response for maneuvers with flat responses, predictions with small constant offsets and small magnitude signals. Nevertheless, it is in most cases an excellent quantitative measure of agreement.

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